DiffRGD: An Inference-Time Diffusion Guidance Through Riemannian Gradient Descent

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ECCV 2026 | MALMÖ | SEPT 8–12

Inference-time Diffusion Control

Image Inverse Problem (IP)

$$\boldsymbol{y} = \mathcal{A}\boldsymbol{x}^{\text{gt}} + \text{noise}$$

Task operator

$$\boldsymbol{y} \approx \mathcal{A}\hat{\boldsymbol{x}}$$

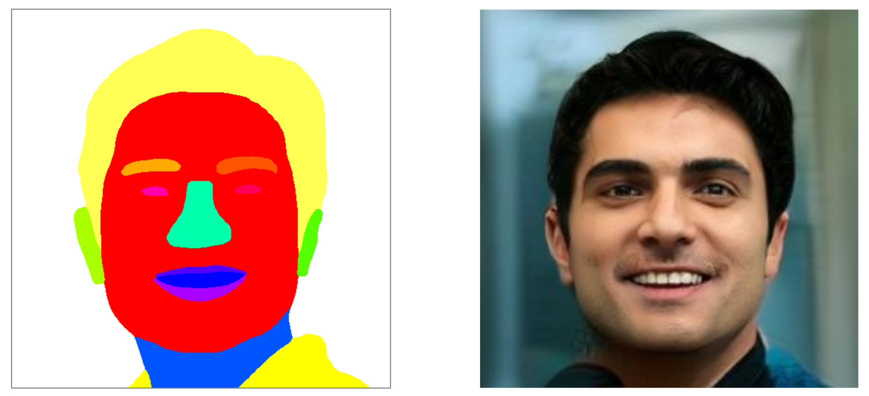
Measurement $\boldsymbol{y}$ Reconstruction $\hat{\boldsymbol{x}}$

$$\mathcal{L}_{\text{IP}}(\boldsymbol{x}, \boldsymbol{y}) = \|\mathcal{A}\boldsymbol{x} - \boldsymbol{y}\|_2^2$$

Conditional Generation (Seg)

ψ : Face Segmenter

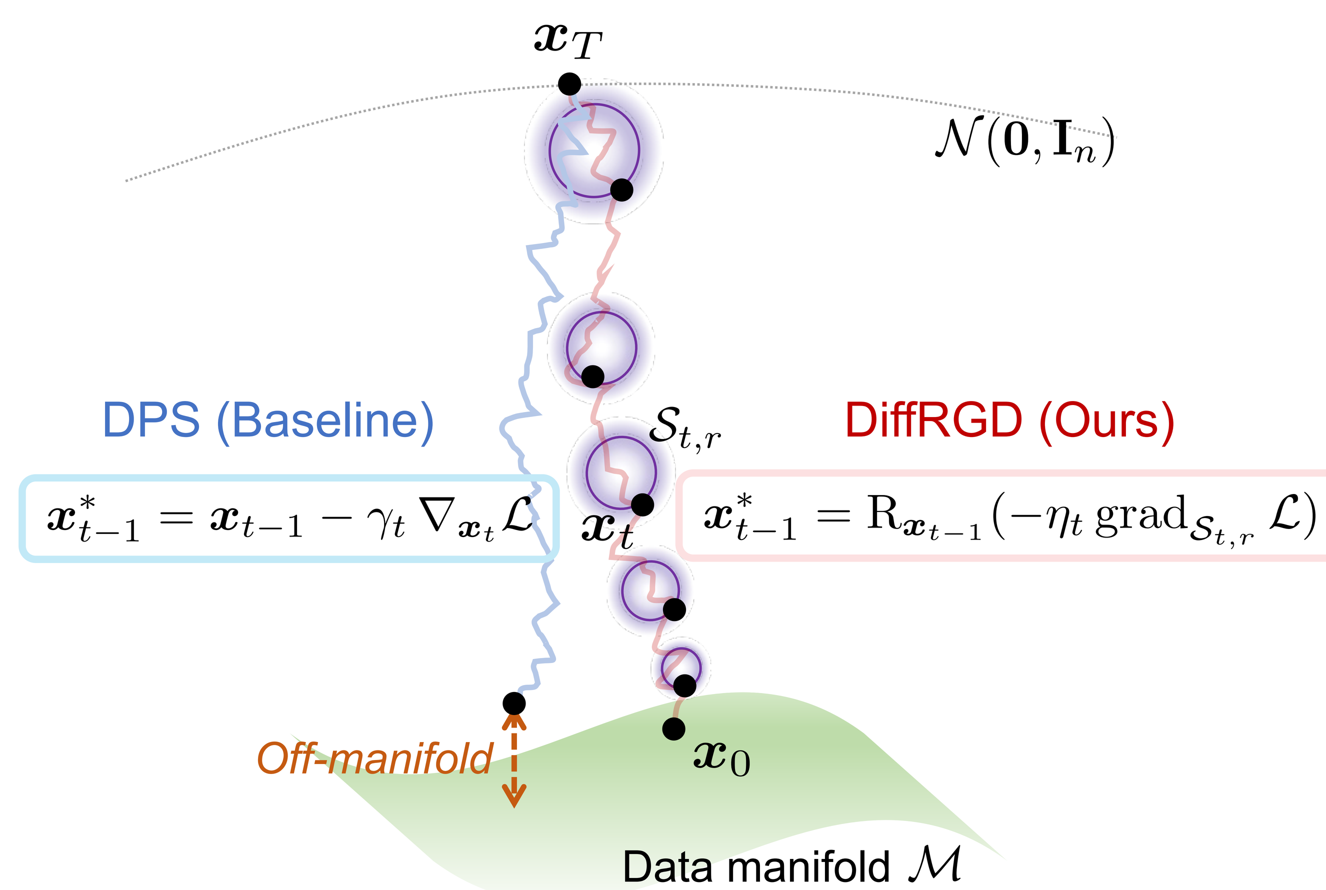
$$\boldsymbol{y} \approx \psi(\hat{\boldsymbol{x}})$$



Condition $\boldsymbol{y}$ Generation $\hat{\boldsymbol{x}}$

$$\mathcal{L}_{\text{Seg}}(\boldsymbol{x}, \boldsymbol{y}) = \|\psi(\boldsymbol{x}) - \boldsymbol{y}\|_2^2$$

$$\hat{\boldsymbol{x}}_{t-1} \sim p_\theta(\boldsymbol{x}_{t-1}|\boldsymbol{x}_t) := \mathcal{N}(\boldsymbol{\mu}_t, \sigma_t^2 \mathbf{I}_n)$$
$$\boldsymbol{x}_{t-1} = \underset{\boldsymbol{x} \in \mathbb{R}^n}{\operatorname{argmin}}\, \mathcal{L}(\hat{\boldsymbol{x}}_0(\boldsymbol{x}, t-1), \boldsymbol{y})$$



1. Different tasks share a unified inference-time guidance formulation.
2. Naive gradient guidance can push latents away from their original distribution.
3. The key challenge is to improve conditional alignment without sacrificing sample quality.

Research Question: *Can we design latent-distribution-aware guidance that ensures the guided sample lies within the original latent distribution?*

Distribution-Induced Geometry

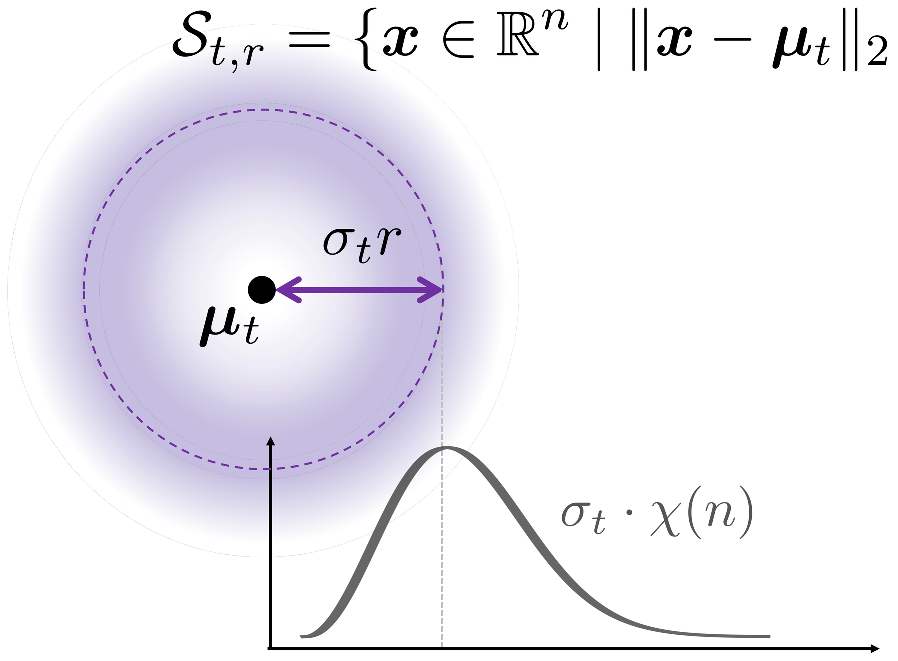
Polar Decomposition of an Isotropic Gaussian

Let $\boldsymbol{x}_{t-1} \sim \mathcal{N}(\boldsymbol{\mu}_t, \sigma_t^2 \mathbf{I}_n)$. Then

$$\boldsymbol{x}_{t-1} = \boldsymbol{\mu}_t + \sigma_t r \boldsymbol{u},$$

where $r \sim \mathcal{X}(n)$ and $\boldsymbol{u} \sim \text{Unif}(\mathbb{S}^{n-1})$.

$$\mathcal{S}_{t,r} = \{\boldsymbol{x} \in \mathbb{R}^n \mid \|\boldsymbol{x} - \boldsymbol{\mu}_t\|_2 = \sigma_t r\}$$

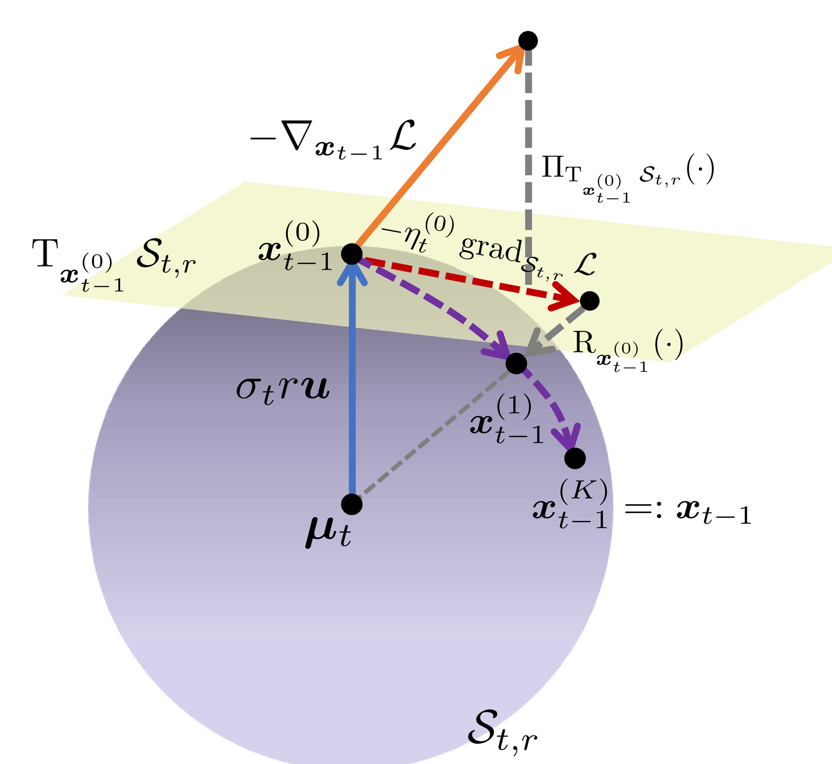


DiffRGD: Diffusion Guidance with Riemannian Gradient Descent

We constrain guidance to a Gaussian-induced spherical manifold and optimize along its geometry.

Riemannian Operators

- Tangent $\mathrm{T}_{\boldsymbol{x}}\mathcal{S}_{t,r} := \{\boldsymbol{v} \in \mathbb{R}^n \mid (\boldsymbol{x} - \boldsymbol{\mu}_t)^\top \boldsymbol{v} = 0\}$
- Projection $\Pi_{\mathrm{T}_{\boldsymbol{x}}\mathcal{S}_{t,r}}(\boldsymbol{v}) := \left(\mathbf{I}_n - \dfrac{(\boldsymbol{x} - \boldsymbol{\mu}_t)(\boldsymbol{x} - \boldsymbol{\mu}_t)^\top}{\|\boldsymbol{x} - \boldsymbol{\mu}_t\|_2^2}\right)\boldsymbol{v}$
- Retraction $\mathrm{R}_{\boldsymbol{x}}(\boldsymbol{v}) := \boldsymbol{\mu}_t + \sigma_t r \cdot \dfrac{\boldsymbol{x} - \boldsymbol{\mu}_t + \boldsymbol{v}}{\|\boldsymbol{x} - \boldsymbol{\mu}_t + \boldsymbol{v}\|_2}$
- Gradient $\operatorname{grad}_{\mathcal{S}_{t,r}} \mathcal{L} := \Pi_{\mathrm{T}_{\boldsymbol{x}^{(k)}_{t-1}}\mathcal{S}_{t,r}}\left(\nabla_{\boldsymbol{x}^{(k)}_{t-1}} \mathcal{L}\right)$

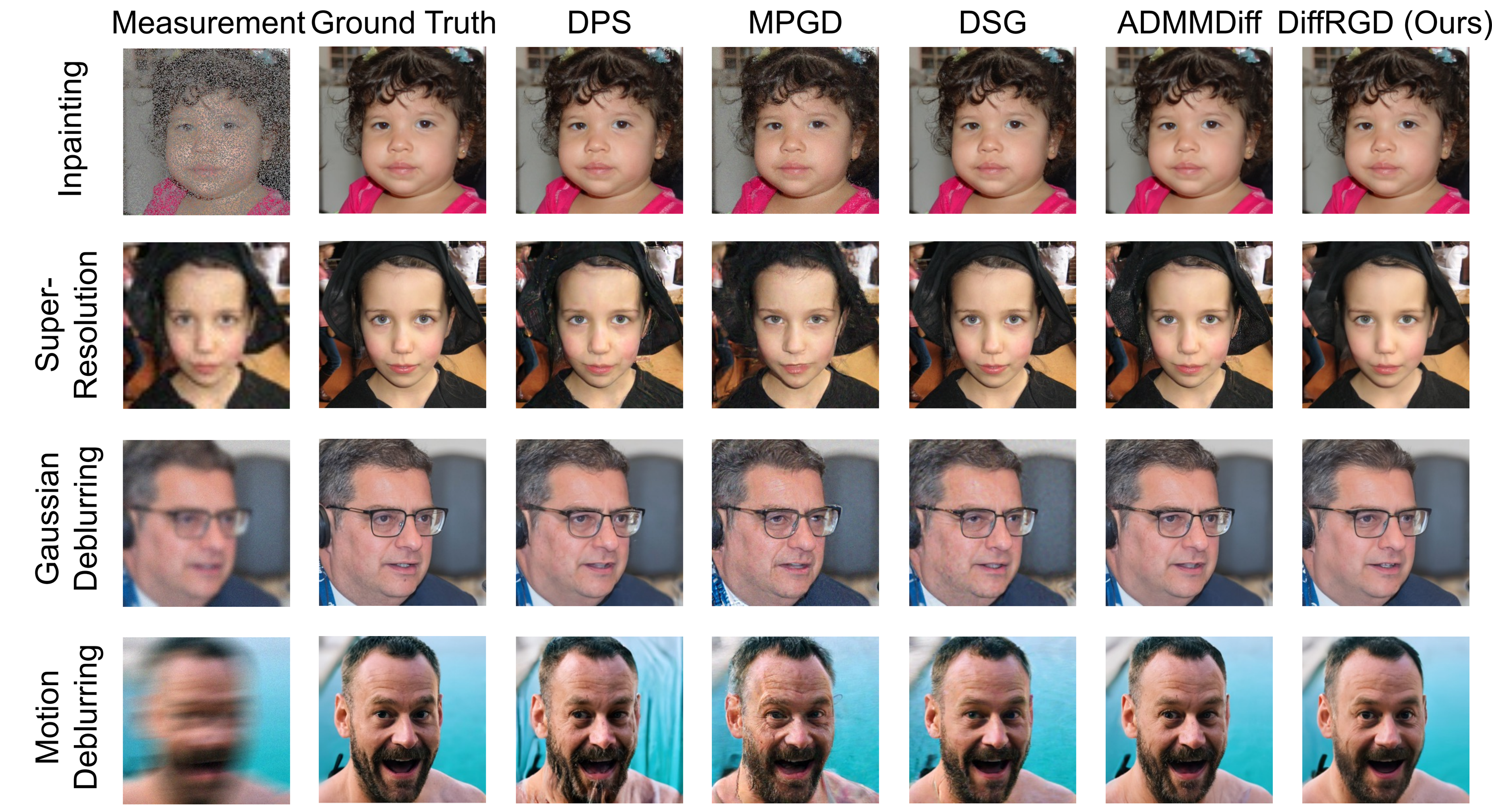


$$\boldsymbol{x}_{t-1} = \underset{\boldsymbol{x} \in \mathcal{S}_{t,r}}{\operatorname{argmin}}\, \mathcal{L}(\hat{\boldsymbol{x}}_0(\boldsymbol{x}, t-1), \boldsymbol{y})$$

$$\boldsymbol{x}^{(k+1)}_{t-1} = \mathrm{R}_{\boldsymbol{x}^{(k)}_{t-1}}\left(-\eta^{(k)}_t \operatorname{grad}_{\mathcal{S}_{t,r}} \mathcal{L}\right)$$

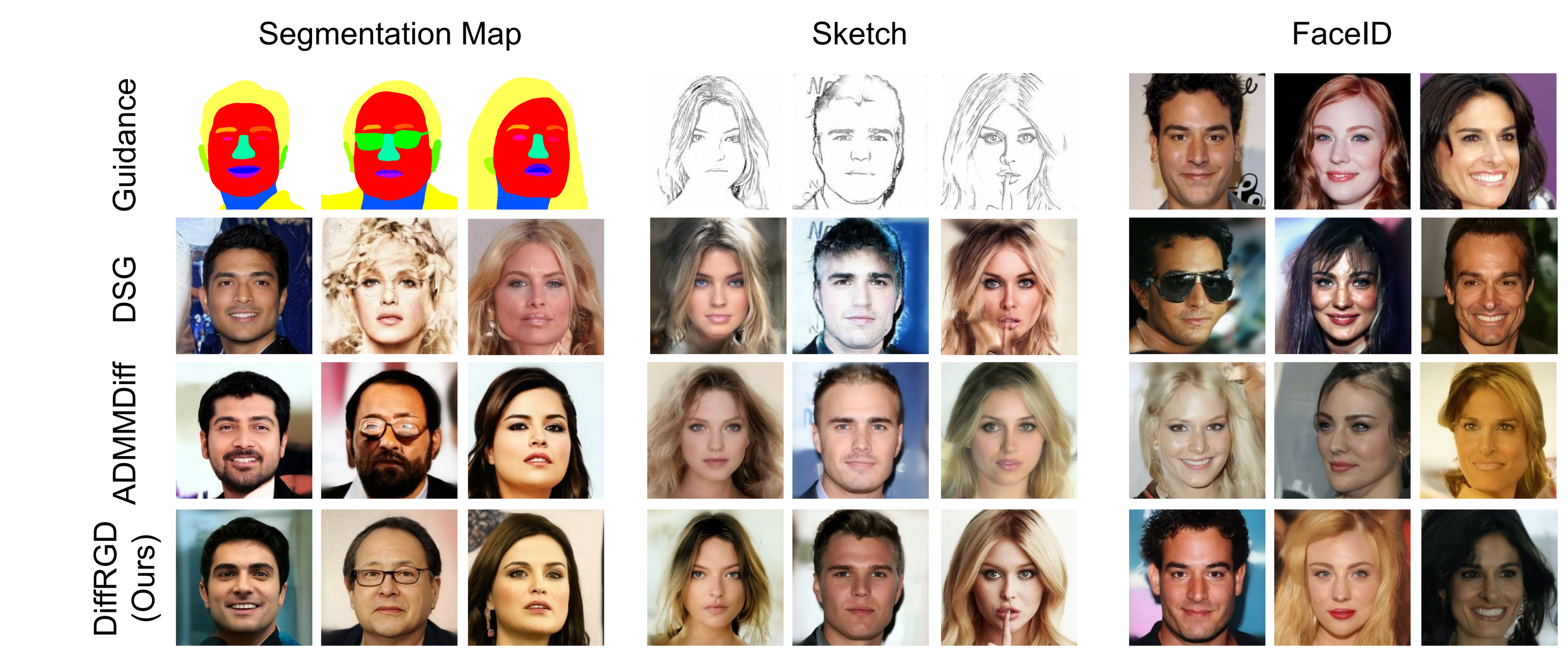
Experimental Results

Linear Inverse Problems



Task	Method	Venue	PSNR ↑	SSIM ↑	LPIPS ↓	FID ↓
Inpainting	DPS (Chung et al., 2023)	ICLR 2023	30.44	0.863	0.153	42.68
	MPGD (He et al., 2024)	ICLR 2024	27.51	0.724	0.256	68.24
	DSG (Yang et al., 2024)	ICML 2024	31.03	0.866	0.144	36.30
	ADMMDiff (Zhang et al., 2025)	CVPR 2025	32.38	0.899	0.119	29.52
	DiffRGD (Ours)	ECCV 2026	**34.04***	**0.926***	**0.096***	**21.88***
Super-Resolution 4×	DPS (Chung et al., 2023)	ICLR 2023	26.03	0.727	0.260	80.05
	MPGD (He et al., 2024)	ICLR 2024	24.40	0.614	0.354	101.50
	DSG (Yang et al., 2024)	ICML 2024	26.71	0.737	0.256	74.67
	ADMMDiff (Zhang et al., 2025)	CVPR 2025	26.48	0.712	0.297	96.69
	DiffRGD (Ours)	ECCV 2026	**27.77***	**0.783***	**0.220***	**63.94***
Gaussian Deblurring	DPS (Chung et al., 2023)	ICLR 2023	25.88	0.721	0.237	69.38
	MPGD (He et al., 2024)	ICLR 2024	24.07	0.576	0.328	95.12
	DSG (Yang et al., 2024)	ICML 2024	**27.45**	0.751	0.259	75.85
	ADMMDiff (Zhang et al., 2025)	CVPR 2025	26.57	**0.757**	0.226	79.30
	DiffRGD (Ours)	ECCV 2026	26.80	**0.757**	**0.218***	**63.83***
Motion Deblurring	DPS (Chung et al., 2023)	ICLR 2023	24.47	0.685	0.271	80.75
	MPGD (He et al., 2024)	ICLR 2024	23.15	0.569	0.357	106.99
	DSG (Yang et al., 2024)	ICML 2024	26.80	0.709	0.290	87.96
	ADMMDiff (Zhang et al., 2025)	CVPR 2025	**27.26**	**0.778**	**0.222**	72.92
	DiffRGD (Ours)	ECCV 2026	25.84	0.736	0.250	**72.26**

Conditional Image Generation



Method	Segmentation Map			Sketch			FaceID		
	mIoU ↑	FID ↓	KID ↓	Sketch-ℓ_2 ↓	FID ↓	KID ↓	FaceID-ℓ_2 ↓	FID ↓	KID ↓
FreeDoM (Yu et al., 2023)	0.622	156.02	0.057	30.85	101.90	0.017	0.557	127.05	0.032
DSG (Yang et al., 2024)	0.750	117.48	0.028	21.36	107.00	0.024	0.340	95.27	0.014
ADMMDiff (Zhang et al., 2025)	0.758	101.86	0.031	30.82	97.52	0.014	0.346	100.81	0.014
DiffRGD (Ours)	**0.804***	**96.10***	**0.026**	**19.48***	**87.82***	**0.012**	**0.303***	**93.80**	**0.011**

Acknowledgements. This research is supported by National Science and Technology Council, Taiwan (R.O.C.), under the grant number of NSTC-113-2115-M-003-012-MY2, NSTC-113-2221-E-002-201, NSTC-113-2221-E-007-105-MY3, NSTC-114-2221-E-001-004, NSTC-114-2221-E-002-182-MY3, NSTC-114-2634-F-001-001-MBK, NSTC-114-2634-F-002-004, and Academia Sinica under the grant number of AS-IAIA-114-M10. We sincerely thank Kang-Yang Huang for the discussions and valuable feedback during the rebuttal stage. We also thank Yu-Hsuan Lin and Hsien-Yueh Huang for their continuous encouragement throughout this project.